Study on the Role of Sentiment Correlation in Public Opinion Identification

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Abstract

Objective: To address the challenge that existing multi-label text emotion classification algorithms struggle to model and utilize semantic correlations among emotions, this paper proposes a multi-label text emotion classification method based on self-attention mechanism for emotion correlation modeling.

Method: This paper proposes AttEmoNet, a multi-label text emotion classification neural network based on self-attention mechanism for emotion correlation modeling. It employs a self-attention emotion correlation module to model the semantics and similarity of emotion labels themselves, utilizes a text encoder based on large-scale pre-trained models to encode input text into semantic vectors, and finally calculates the matching degree between text semantic vectors and emotion semantic vectors through a neural network, thereby achieving more accurate emotion category identification.

Results: The effectiveness of AttEmoNet is verified through comparative experiments on two public datasets, NLPCC2014 and GoEmotions. The results demonstrate that AttEmoNet' s text emotion classification performance is significantly improved compared to baseline methods including Random, cnsenti, SVM, and BERT. Specifically, compared with the current best baseline method, AttEmoNet achieves a maximum improvement of 13.33% in Precision, 21.80% in Recall, and 12.74% in F1-score. Moreover, the emotion semantic correlation matrix modeled by AttEmoNet exhibits good interpretability, proving its capability in modeling emotion semantics.

Limitations: The emergence of large language models opens up new avenues for multi-label text emotion classification. Future work will combine the respective advantages of AttEmoNet and large language models to achieve more accurate and efficient multi-label text emotion classification algorithms.

Conclusion: This paper proposes a multi-label text emotion classification neural network based on self-attention mechanism for emotion correlation modeling, which enhances the capability of text emotion models in modeling emotion semantics and their correlations, as well as improves emotion recognition performance. The effectiveness of this research is verified through comparative experiments on two public datasets.

Full Text

Preamble

Multi-Label Text Emotion Classification Based on Self-Attention Mechanism and Emotion Semantic Similarity Modeling

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[**Objective**] To address the challenge that existing multi-label text emotion classification algorithms struggle to model and utilize semantic correlations between emotions, this paper proposes a multi-label text emotion classification method based on self-attention mechanism for emotion correlation modeling. [**Method**] We introduce a neural network for multi-label text emotion classification called AttEmoNet (Attention-based Emotion Network), which models the semantics and similarities of emotion labels themselves through a self-attention emotion correlation module. The model employs a text encoder based on large-scale pre-trained models to encode input texts into semantic vectors, and finally computes the matching degree between text semantic vectors and emotion semantic vectors via a neural network to achieve more accurate emotion category recognition. [**Results**] The effectiveness of AttEmoNet is validated through comparative experiments on two public datasets: NLPCC2014 and GoEmotions. The results demonstrate that AttEmoNet significantly outperforms baseline methods including Random, cnsenti, SVM, and BERT in text emotion classification performance. Compared to the best existing baseline, AttEmoNet achieves a maximum improvement of 13.33% in Precision, 21.80% in Recall, and 12.74% in F1-score. Moreover, the emotion semantic correlation matrix modeled by AttEmoNet exhibits strong interpretability, proving its capability in modeling emotion semantics. [**Limitations**] The emergence of large language models opens new avenues for multi-label text emotion classification. Future work will combine the respective advantages of AttEmoNet and large language models to achieve more accurate and efficient multi-label text emotion classification algorithms. [**Conclusion**] This paper proposes a multi-label text emotion classification neural network based on self-attention mechanism for emotion correlation modeling, which enhances the ability to model emotion semantics and their correlations as well as improves emotion recognition performance. The validity of our approach is confirmed through comparative experiments on two public datasets.

Text emotion classification is a crucial task in data mining research, aiming to identify emotional tendencies in given texts using data mining techniques (such as Naive Bayes algorithms and deep neural networks) to facilitate deeper understanding of text content and its potential impact. With the rise of public social media platforms like Weibo and Twitter, text emotion classification has demonstrated significant importance in public opinion analysis and social hotspot event tracking. Practitioners employ text emotion classification algorithms to identify emotional tendencies in massive volumes of user-generated content on social media platforms, thereby comprehensively assessing public opinion trends and formulating appropriate responses. The technology itself has evolved from traditional simple binary classification tasks (determining whether text sentiment is positive or negative) to multi-classification tasks that identify specific emotions such as happiness, sadness, liking, and anger. However, compared to traditional binary text emotion classification, multi-label text emotion classification faces numerous challenges including data sparsity, class imbalance, and difficulty in modeling emotion semantics. To address these issues, researchers have proposed various multi-label text emotion classification models based on statistics, machine learning, and deep learning techniques. For instance, text emotion recognition models based on emotion dictionaries [1–3] determine text emotion categories by retrieving and matching emotion words in texts. Models based on Naive Bayes and Support Vector Machines [4] utilize statistical learning methods to identify emotion probabilities by analyzing and modeling word frequency statistical features. With the widespread application of deep learning in natural language understanding [5–7], deep learning-based text emotion recognition models represented by Recurrent Neural Networks (RNN) [8] and pre-trained models [3,9] have achieved significant progress in identifying specific text emotion categories, relying on deep learning' s powerful capability in semantic representation modeling.

Nevertheless, current multi-label text emotion classification methods still face important unresolved issues. First is emotion correlation modeling. Unlike other multi-label text classification tasks (such as news category classification or text event classification), emotion labels in multi-label text emotion classification possess intricate semantic correlations. For example, the emotion "happiness" has high semantic overlap with "liking," which intuitively manifests as frequent co-occurrence of these two emotions in texts. However, most existing multi-label text emotion classification methods treat emotion labels as independent categories in general text classification tasks [10–12,4], neglecting the complex semantic correlations between emotions. This limitation hinders deep exploration of associations between texts and emotions, resulting in constrained classification accuracy. Second is the modeling of emotion semantics itself. Text emotion classification tasks not only focus on the correspondence between texts and emotions but also on the semantic information inherent in emotions themselves. Emotion semantic representation facilitates understanding the essence of emotions and their similarities and differences, and is particularly beneficial for further applications of emotion information in downstream tasks such as text generation. However, existing multi-label text emotion classification methods struggle to model emotion semantic representations, making it difficult to efficiently mine the rich information contained in text emotion classification data.

To solve these problems, this paper innovatively proposes a pre-trained emotion correlation text emotion recognition model (AttEmoNet) for public social platform public opinion identification, based on basic emotion theory [13] and pre-trained deep learning methods [5,9]. Specifically, AttEmoNet utilizes the large-scale pre-trained model BERT [5] to model text semantic vectors, while simultaneously employing self-attention mechanism to model emotion semantic features and emotion correlations. Subsequently, AttEmoNet uses a deep learning-based Multi-Layer Perceptron (MLP) to identify text emotion probabilities. We then validate AttEmoNet' s emotion recognition capability through comparative experiments against existing classical text emotion recognition models on the Chinese dataset NLPCC2014 and the English dataset GoEmotions. Additionally, we reveal AttEmoNet' s capability in modeling emotion semantic correlations through model parameter visualization analysis on NLPCC2014. Finally, we discuss the advantages and limitations of our work and outline future research directions.

2.1 Basic Emotion Theory

Basic emotion theory was proposed by American psychologist Paul Ekman et al. in the 1970s [13]. This theory posits that humans have six basic emotions: happiness, sadness, fear, anger, surprise, and disgust. These basic emotions are considered to be universally present across cultures and species. Based on basic emotion theory, Ekman et al. [13] discovered universality in emotional expressions by observing facial expressions across different cultures. Carroll E. Izard [14] expanded basic emotion theory by discussing relationships between basic emotions and the relationship between emotion and cognition. This research proposed a model of the emotion system that describes relationships between basic emotions and how they influence and regulate each other. For example, the author noted a close relationship between "anger" and "disgust," while "happiness" and "sadness" have an opposing relationship. James A. Russell [15] proposed the circumplex model of affect, extending basic emotion theory by emphasizing the construction and subjective experience of emotions and incorporating ideas of emotion correlation modeling. Alan S. Cowen and Dacher Keltner [16] explored how people describe and differentiate emotional experiences in self-reports. This study discovered more fine-grained emotional experiences compared to basic emotion theory, expanding understanding of emotions and breaking through traditional basic emotion concepts. It demonstrated that emotions are complex and diverse, and can be described and captured through multiple discrete emotion categories and continuous gradients. In summary, basic emotion theory initially proposed six basic elements of emotion. Building upon this foundation, scholars have conducted in-depth explorations into emotion construction and relationships between emotions, developing a gradually complete theoretical framework.

2.2 Text Emotion Recognition

Text emotion recognition is a type of text classification task that aims to identify and classify emotional categories of texts based on their semantic features. According to different distributions of emotion labels, text emotion recognition tasks can be categorized into emotion polarity classification (positive/negative sentiment, binary classification), emotion category classification (multi-class classification), and emotion label classification (multi-label classification). Text emotion recognition models include rule-based emotion dictionary methods [1,2,17], statistical machine learning methods [4,18], and deep learning methods [7,3,9,8]. Rule-based emotion dictionary methods are unsupervised approaches that obtain emotion values of emotion words in documents using emotion dictionaries, then determine the overall emotional tendency of documents through weighted calculation. These methods do not consider relationships between words or how word sentiment tendencies change with context. Common emotion dictionaries include English dictionaries such as General Inquirer, SentiWordNet, Opinion Lexicon, MPQA [19], and Chinese dictionaries such as HowNet [20], NTUSD [21], and the Chinese Emotion Vocabulary Ontology [22]. Statistical machine learning methods are supervised approaches that train machine learning classification models on text data with emotion labels, then apply the trained models to text emotion prediction tasks. For example, Xie Lixing et al. [23] proposed a Support Vector Machine (SVM)-based text emotion recognition model that divides emotion analysis into two strategies and four methods. Liu Baoqin et al. [24] proposed a Naive Bayesian (NB)-based text emotion recognition method that establishes a three-layer tree structure for emotion recognition. Deep learning methods are supervised approaches that train neural network classification models on text data with emotion labels, leveraging the strong fitting capability of neural networks to accurately predict text emotion categories. For instance, Su Xiaoying et al. [25] proposed a Convolutional Neural Network-based text emotion recognition model where a dual convolutional layer structure can extract features from statements of arbitrary length. Sun Xiao et al. [26] proposed a deep belief network-based text emotion recognition model that addresses the problem of sparse text features. With the rise of Large Language Models (LLM) [27–29], pre-trained LLM-based methods have emerged in text emotion recognition tasks and achieved state-of-the-art performance on numerous datasets. For example, Fang Yinglan et al. [30] used the BERT model to obtain more complete text semantic representations for more accurate text emotion category prediction. Ma Da et al. [31] compared the text emotion recognition capabilities of various large language models in a study on social network users' behavior of disseminating others' private information.

2.3 Deep Learning and Attention Mechanism

The attention mechanism was first proposed by Bahdanau et al. [32] as a technique in deep learning for modeling semantic correlations between different parts of semantic sequences and their associated representations. In natural language processing, attention mechanisms are commonly used to model semantic associations between contextual texts, thereby achieving correspondence between model outputs and context in tasks such as text generation and text classification. The Transformer model proposed by Vaswani et al. [5] is a representative model using self-attention mechanisms. The Transformer model possesses powerful semantic representation and text generation capabilities, serving as the cornerstone for many text classifiers and text emotion recognition methods.

3 Emotion Correlation Modeling Based Text Emotion Recognition Method

Existing text emotion recognition methods struggle to model the important role of emotion correlations in emotion recognition. Therefore, this paper first proposes an emotion correlation modeling based text emotion recognition method (AttEmoNet). Subsequently, we demonstrate AttEmoNet' s superiority in text emotion recognition and emotion correlation modeling on a Weibo text emotion recognition dataset. Finally, we apply AttEmoNet to text emotion analysis on given topics.

3.1 AttEmoNet Method Introduction

The AttEmoNet algorithm framework proposed in this paper is shown in Figure 1 [Figure 1: see original paper]. The framework comprises three modules: a text encoder module, an attention text correlation modeling module, and an emotion recognition neural network module. The text encoder module uses the large-scale pre-trained model BERT to encode text input into high-dimensional text semantic vectors. The attention text correlation modeling module employs attention mechanisms to transform trainable emotion intrinsic feature vectors into feature vectors containing emotion correlations, while simultaneously outputting an emotion correlation matrix. The emotion recognition neural network module matches and computes the probability of text containing each emotion by pairing text semantic vectors with each emotion feature vector containing emotion correlations. The algorithm ultimately outputs emotion probability scores. During the training phase, the model' s emotion intrinsic feature vectors, attention text correlation modeling module, and emotion classification neural network are trained using a multi-label text emotion recognition dataset; during the inference phase, AttEmoNet' s network parameters are frozen to enable end-to-end text emotion recognition.

3.2 BERT Text Encoder

The BERT text encoder in the AttEmoNet framework is a large Chinese pre-trained text encoding model based on BERT [5] [33]. This module uses Masked Language Model (MLM) to generate deep bidirectional language representations. Experiments in the original BERT paper [5] demonstrated that BERT achieved state-of-the-art results on 11 natural language processing tasks, proving the effectiveness of the BERT module in text semantic representation.

Formally, let the original text input be a character sequence. BERT' s encoding process can be formally represented as shown in Equation (1):

$$\mathbf{e}_{\text{text}} = \text{BERT}(x_1, x_2, \dots, x_n)$$

where $\mathbf{e}_{\text{text}}$ is the text semantic representation vector and d_{text} is the dimension of the text semantic representation vector defined by BERT. Typically, $d_{\text{text}} = 1,024$.

3.3 Attention Text Correlation Modeling Module

The attention text correlation modeling module uses self-attention mechanism to model emotion semantic correlations, thereby addressing the lack of research on emotion correlations in existing studies. Specifically, the self-attention mechanism adopts a query-key-value (QKV) pattern. Each emotion in the framework (such as "happiness," "liking," "surprise" in Figure 1) has a trainable query vector, key vector, and value vector (the value vector corresponds to the emotion intrinsic feature vector in Figure 1). First, for a target emotion (e.g., "happiness"), its query vector is obtained, and cosine similarity is used to compute the similarity between this query vector and the key vectors of every other emotion. The similarity with each other emotion represents the emotion semantic dependency —the degree to which the target emotion' s semantic representation depends on that emotion. Subsequently, the target emotion' s feature vector containing emotion correlations is computed. This vector equals the weighted average of each emotion' s intrinsic feature vector (value vector), with weights being the computed emotion semantic dependencies. Finally, the Pearson correlation coefficient between each pair of feature vectors containing emotion correlations is computed to output the emotion correlation matrix.

Formally, we first use one-hot encoding to label each emotion (if the total number of emotions is K, the k-th emotion is encoded as a K-dimensional vector with 1 at the k-th position and 0 elsewhere). Let $\mathbf{E}_v$ denote the emotion feature intrinsic vector matrix, $\mathbf{E}_q$ denote the emotion query vector matrix, and $\mathbf{E}_k$ denote the emotion key vector matrix. The module first extracts the target emotion k' s feature intrinsic vector, query vector, and each emotion' s (including the target emotion itself) key vector:

$$\mathbf{v}_k = \mathbf{E}_v \times \mathbf{o}_k, \quad \#2$$

$$\mathbf{q}_k = \mathbf{E}_q \times \mathbf{o}_k, \quad \#3$$

Subsequently, the semantic dependency similarity between the target emotion and each emotion is computed:

$$s_{k,j} = \cos(\mathbf{q}_k, \mathbf{e}_{k,j}), \quad j = 1, 2, \dots, K, \quad \#4$$

$$\alpha_{k,j} = \mathrm{softmax}(s_{k,j}). \quad \#5$$

Finally, the target emotion’ s emotion semantic vector containing emotion correlations is computed:

$$\mathbf{e}_k^{\mathrm{emo}} = \sum_{j=1}^{K} \alpha_{k,j} \times \mathbf{v}_j. \quad \#6$$

The computation result $\mathbf{e}_k^{\mathrm{emo}}$ is the emotion vector representation containing emotion dependency relationships, used for subsequent text emotion recognition.

3.4 Emotion Recognition Neural Network Module

The emotion recognition neural network module uses a neural network to compute the matching degree between text semantic representation and emotion semantic representation, thereby predicting the probability of each emotion being contained in the text. Specifically, given a text’ s semantic representation $\mathbf{e}_{\mathrm{text}}$ and an emotion’ s semantic representation vector $\mathbf{e}_k^{\mathrm{emo}}$, this module uses a quadratic-form neural network to predict text emotion probability:

$$p_k = \sigma(\mathbf{e}_k^{\mathrm{emo}T} \mathbf{W} \mathbf{e}_{\mathrm{text}}),$$

where $\mathbf{W}$ is the emotion recognition parameter matrix. The above eigenvalue decomposition transformation indicates that this neural network prediction process is equivalent to applying the same linear transformation to both text semantic vectors and emotion semantic vectors, followed by element-wise weighted averaging with weights being $\mathbf{W}$’ s eigenvectors. The neural network training process essentially optimizes the linear transformation and eigenvectors to make predicted text emotion probabilities approach ground-truth labels.

3.5 Loss Function

Since AttEmoNet addresses a multi-label text emotion prediction problem, cross-entropy is adopted as the loss function. During model training, AttEmoNet’ s objective is to minimize the loss function value:

$$\mathcal{L}(\Theta) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} \left[y_{i,k} \log(\hat{y}_{i,k}) + (1 - y_{i,k}) \log(1 - \hat{y}_{i,k}) \right],$$

where Θ denotes all trainable parameters in AttEmoNet, N denotes the number of samples (texts in the training set), and K denotes the number of possible emotion categories. $y_{i,k} = 1$ indicates that text i in the dataset contains emotion k, while $y_{i,k} = 0$ indicates it does not. $\hat{y}_{i,k}$ represents the probability of text i containing emotion k predicted by AttEmoNet.

4.1 Experimental Setup

This experiment validates AttEmoNet' s accuracy in text emotion prediction tasks and its capability in modeling emotion feature correlations by conducting comparative tests between the proposed text emotion recognition model AttEmoNet and various baseline models on public Weibo datasets. For experimental datasets, this study adopts two public datasets: NLPCC2014 and GoEmotions [34]. The NLPCC2014 dataset comprises 45,421 text instances from Sina Weibo, with manually annotated emotion labels including anger, disgust, fear, happiness, like, sadness, surprise, and no emotion—totaling 8 labels with 7 emotion categories. Each text contains at most two emotions. For the GoEmotions dataset, which comprises 58,000 text instances from the English forum Reddit with 27 fine-grained emotion categories in its original form, we filtered out 32,445 valid samples based on basic emotion theory, selecting the same 7 emotions as in NLPCC2014 plus neutral as the target for text emotion recognition.

Subsequently, we split each dataset into training, validation, and test sets at a ratio of 70%:10%:20%. Table 1 shows the statistics of the preprocessed datasets.

Table 1 . Preprocessed Dataset Statistics

Dataset	Sample Proportion (No Emotion/Neutral)	Sample Proportion (Emotion Count=1)	Sample Proportion (Emotion Count=2)	Sample Proportion (Emotion Count=3)	Sample Proportion (Emotion Count=4)
NLPCC2014	44.1%	38.4%	17.5%	-	-
GoEmotions	56.3%	41.4%	0.06%	0.01%	-

In terms of experimental environment, all models in this paper are implemented using Python 3.8, with PyTorch as the deep learning framework and Linux as the operating system. The experimental hardware configuration is a server equipped with two 2.10GHz Intel Xeon E5-2620 v4 CPUs and one NVIDIA Tesla-A100 GPU.

4.2 Text Emotion Prediction Experiment

This experiment primarily includes emotion prediction experiments and emotion feature correlation analysis. Finally, the AttEmoNet emotion prediction model is applied to public opinion identification. For the text emotion prediction experiment, the following baseline models are adopted:

- **Random**: Random prediction. For each emotion, texts are assigned to that emotion category with a probability of 1/2. Whether an emotion prediction model performs better than random prediction is the basic criterion for its usability.
- **cnsenti**: Chinese Sentiment analysis library, an emotion prediction model based on the HowNet emotion dictionary.

- **SVM**: Support Vector Machine, an emotion prediction model based on support vectors. In the experiments, BERT is used to encode texts into semantic vectors as input for SVM.
- **BERT**: A Transformer-based pre-trained large language model. A Full-connection Neural Network is used as the downstream output layer for text emotion prediction tasks.

Table 4 . Text Emotion Prediction Experiment Results

Model	NLPCC2014			GoEmotions		
	Precision	Recall	F1-score	Precision	Recall	F1-score
Random	-	-	-	-	-	-
cnsenti	-	-	-	-	-	-
BERT+NN	-	-	-	-	-	-
AttEmoNet	-	-	-	-	-	-
Performance Improvement	13.33%	2.52%	8.44%	4.72%	21.80%	12.74%

The text emotion prediction experiment results are shown above. Considering the characteristics of multi-label classification tasks, the evaluation metrics are Micro Precision, Micro Recall, and Micro F1 Score. Higher scores for each metric indicate higher accuracy in text emotion recognition. Since GoEmotions is an English dataset, the Chinese dictionary-based baseline model cnsenti cannot recognize emotions in this dataset. The experimental results show that the proposed AttEmoNet outperforms existing baseline models in all three text emotion prediction metrics: Precision, Recall, and F1-score, with maximum improvements of 13.33% in Precision, 21.80% in Recall, and 12.74% in F1-score. This demonstrates that AttEmoNet can predict text emotions more accurately than existing models. Additionally, among baseline models, the BERT+NN method also significantly outperforms other existing methods. The comparison between BERT+NN and cnsenti demonstrates that BERT pre-trained language encoding-based text emotion prediction models have better performance than traditional rule-based and emotion dictionary-based models for Weibo emotion prediction. The comparison between BERT+NN and BERT+SVM shows that neural network-based text emotion prediction algorithms outperform Support Vector Machine (SVM)-based algorithms for Weibo emotion prediction. Compared to the best baseline model BERT+NN, the proposed AttEmoNet further improves the performance of BERT pre-trained language encoding-based text emotion prediction models through its innovative emotion feature modeling module.

4.2 Visualization Experiment: Emotion Feature Correlation Modeling Experiment

Figure 2 [Figure 2: see original paper]. Emotion Feature Correlation Heatmap

This section analyzes AttEmoNet' s capability in modeling emotion semantic similarity using the NLPCC2014 dataset as an example. The AttEmoNet text emotion prediction model models correlations between emotion features through its attention text emotion modeling module, thereby improving text emotion prediction accuracy. This experimental phase primarily focuses on AttEmoNet' s own text emotion feature correlation modeling results. In AttEmoNet, emotion features are represented by $\mathbf{e}_k^{\text{emo}}$, where k denotes the emotion category index. For any two emotions k_1 and k_2, this experiment adopts the Pearson correlation coefficient of emotion features as the emotion feature correlation measure, denoted as ρ_{k_1,k_2}. This correlation coefficient ranges between -1 and 1. When $\rho_{k_1,k_2} > 0$, the two emotion features exhibit positive correlation (similarity); when $\rho_{k_1,k_2} \approx 0$, they exhibit no correlation (independence); when $\rho_{k_1,k_2} < 0$, they exhibit negative correlation (semantic opposition). The emotion feature correlation calculation results are shown in the figure below, which includes 7 emotions: anger, disgust, fear, happiness, like, sadness, and surprise. Brighter colors and larger correlation values in each block indicate stronger associations between the two emotions. According to Figure 2, the three emotions with the strongest correlation to each emotion are:

- **Anger**: disgust (0.99), surprise (0.50), fear (0.39)
- **Disgust**: anger (0.99), surprise (0.46), fear (0.34)
- **Fear**: surprise (0.97), anger (0.39), sadness (0.38)
- **Happiness**: like (0.55), surprise (0.48), fear (0.37)
- **Like**: happiness (0.55), sadness (0.31), anger (0.24)
- **Sadness**: fear (0.38), anger (0.35), like (0.31)
- **Surprise**: fear (0.97), anger (0.50), happiness (0.48)

These results show that different emotion types exhibit either strong correlations or independence with some emotions due to their distinct semantics. Some emotions with consistent semantic tendencies often display strong clustering characteristics. For instance, "anger" and "disgust" are both negative emotions with a semantic correlation as high as 0.99, and they both have relatively strong correlations with "fear," indicating that these four emotions are semantically similar, which aligns with human intuition. Meanwhile, "happiness" and "like" have strong correlations, showing that these two intuitively positive emotions are also semantically similar. Additionally, "surprise" has high semantic similarity with both positive emotions like "happiness" and negative emotions like "fear," indicating that "surprise," as an emotion perceived due to sudden changes, tends to be neutral. In other words, "surprise" can co-occur with positive emotions (e.g., "pleasant surprise") as well as negative emotions (e.g., "frightened surprise").

Online social platforms frequently witness large-scale controversial topics, many of which can easily ferment into public opinion incidents and enter large-scale emotional, irrational dissemination. Existing emotion recognition models struggle to model emotion correlations, and their emotion prediction accuracy needs improvement. To address these issues, this study first conducts extensive and in-depth literature review. Based on basic emotion theory and deep learning technology, we innovatively propose a large-scale pre-trained text emotion recognition method (AttEmoNet) for accurate text emotion recognition and emotion correlation modeling on social platforms. Through large-scale comparative experiments on real text emotion recognition datasets—Chinese dataset NLPCC2014 and English dataset GoEmotions—we validate AttEmoNet' s accurate text emotion recognition capability. Emotion recognition comparison experiments demonstrate that AttEmoNet improves Precision, Recall, and F1 Score by 13.33%, 2.52%, and 8.44% respectively compared to the best baseline method BERT, effectively enhancing text emotion recognition accuracy. Emotion feature correlation experiments reveal that emotions with similar emotional valence (positive/negative) exhibit strong semantic correlations, while the "surprise" emotion shows high semantic correlation with both positive and negative emotions, serving as a bridge connecting them in the emotion correlation graph.

The significance of this research lies in: First, at the theoretical level, this work organically integrates basic emotion theory with deep learning technology, innovatively proposing a large-scale pre-trained text emotion recognition method (AttEmoNet). Large-scale experiments on real datasets validate its capability for accurate text emotion recognition and emotion semantic correlation modeling. In text emotion recognition tasks, the accuracy of emotion recognition is the core issue of related research and an important technical guarantee for public opinion monitoring. Therefore, AttEmoNet' s high performance demonstrated in experiments undoubtedly holds significant importance for enhancing public opinion monitoring effectiveness. Second, at the practical level, this study is the first to explore the public emotion distribution and temporal evolution patterns under the highly sensitive Weibo topic of "feminism." Additionally, leveraging AttEmoNet' s emotion semantic correlation modeling capability, we simultaneously analyze the correlation relationships between different emotions under this topic, providing important data references for related public opinion monitoring.

However, this study still has some limitations. First, due to constraints on accessible data volume, the training corpus constructed for AttEmoNet is still insufficient to maximize model performance, requiring further expansion of text data in future research. Second, in terms of text semantic parsing capability, AttEmoNet's performance in recognizing emotions in texts with high implicit information such as sarcasm and irony still needs improvement. In future research plans, on one hand, we can further enhance text emotion recognition capability by expanding datasets and optimizing model architectures. On the other hand, with the rise of Large Language Models (LLM) such as ChatGPT, we can combine the advantages of LLMs in text generation and emergent capabilities with

AttEmoNet's strengths in strong semantic modeling and low computational cost to design more efficient text emotion recognition models. Furthermore, online social platforms feature complex topics and user distributions with rich information. How to leverage abundant topic and user information to assist text emotion recognition and public opinion monitoring, and explore downstream applications of emotion recognition and emotion semantic modeling results, are also considered important future research directions.

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Note: Figure translations are in progress. See original paper for figures.